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NEURAL NETWORK FOR NON-SMOOTH NONLINEAR APPROXIMATION

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ABSTRACT

A performance analysis is presented of extended minimal resource allocating neural network algorithm for online compensation of the nonlinearity of backlash. The results indicate that the algorithm realizes network using fewer hidden neurons. The modification reduces the computation load for minimum resource allocating neural network and leads to considerable reduction in the approximation time. Results show that this network is well suited for fast online approximation.

Keywords **-** neural network; radial basis function; backlash

1. INTRODUCTION

Nonlinearities are available in control systems frequently due to the nature of most physical systems. Many physical components of control systems have non-smooth nonlinear characteristics such as dead-zone, hysteresis, saturation, friction, backlash and various nonlinear relations between system variables. The adaptive control of nonlinear systems has recently made significant advances. A wide range of adaptive controlling schemes has been developed for special classes of nonlinear systems [1]. For complex process, however, the forms of the system equations may be unknown, making it impossible to determine the required control law for use in the existing adaptive control procedure. This problem provides the motivation for considering the use of neural networks in adaptive control [2].
The most common NN architectures used in nonlinear control applications are the multilayer perceptron (MLP) and the radial basis function (RBF) NN. It is known that the use of feed forward neural network with the back propagation (BP) learning algorithm causes problems with local minima, saddle points and the algorithm itself has a very slow convergence rate. Thus, its use is limited to off-line training applications. Since the early nineties, RBF NN's with Gaussian function have been widely used as the basic structure of the neural networks in nonlinear control, due to its good global generalization ability and simple network structure that avoid unnecessary and lengthy calculations [3, 4].
In this work, we investigated the performance of the radial basis function neural network for non-smooth nonlinear approximation. The neural net work is trained on-line to approximate the nonlinearity of backlash. The results are presented to illustrate the advantages of the proposed neural network.

2. RADIAL BASIS FUNCTION NEURAL NETWORK (RBF NN)

Radial Basis Function Neural Network (RBF-NN) with Gaussian functions have good local interpolation and global generalization, thus they have extensively been used as the basis of NN for nonlinear system

$$\hat{y}(\boldsymbol{x}, \boldsymbol{j}) = w_0 + \sum_{i=1}^{N} w_i \exp\left[\frac{-1}{\sigma_i^2}\left\|\boldsymbol{x} - \mu_i\right\|^2\right];$$

$$\boldsymbol{j} = [w_0 \ldots . w_N, \mu_1 \ldots . \mu_N, \sigma_1 \ldots . \sigma_N],$$

identification and control. This Neural Network is simply a two-layer feedforword structure as shown in Figure 1. In case of a Gaussian function, the output of the RBF-NN is expressed as:
where (w, μ, σ) are the weights, centers and widths, respectively; N – Number of nerons; $\boldsymbol{x}$ – input vector; $\boldsymbol{j}$ – vector comprises the set parameters to be tuned by a learning algorithm.

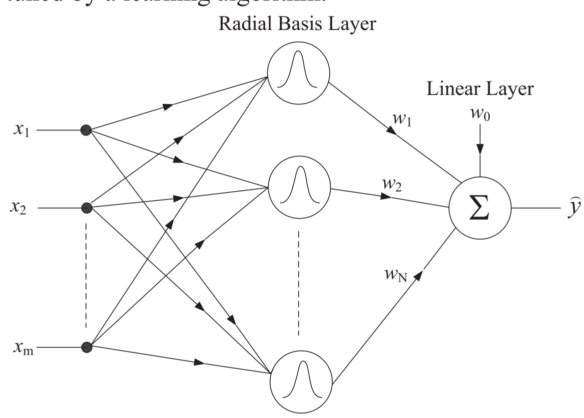

Figure 1 : Radial Basis Function Neural Network

In 1991, platt proposed a sequentional learning algorithm to overcome the problem of increasing neurons where the emphasis was to learn quickly, generalize well and have a compact representation. He proposed a resource allocating network (RAN) algorithm, which allocates hidden neurons automatically on the basis of the novelty of the new data and optimizes the parameters of the network using a gradient decent algorithm [5]. A further improvement to RAN was a pruning strategy to avoid an excessive increase in the size of the neural network. The resulting network is called the Minimal Resource Allocating Network (MRAN), which enhances RBF-NN application with growth and pruning features. In order to reduce the computation load, the Extended Minimal Resource Allocating Network (EMRAN) was developed. In this network, the most activated neuron is updated so as to realize a scheme for fast on-line identification and control

3. NON-SMOOTH NONLINEARITY APPROXIMATION USING EMRAN-RBF NN

The nonlinearity approximation mechanism is shown in Figure 2. The unknown nonlinearity and the NN are subjected to an input and the error between the actual output and the predicted output is used to adjust the parameters of EMRAN-RBF NN. After a period of training, the NN will produce approximately the same response as the actual nonlinearity.

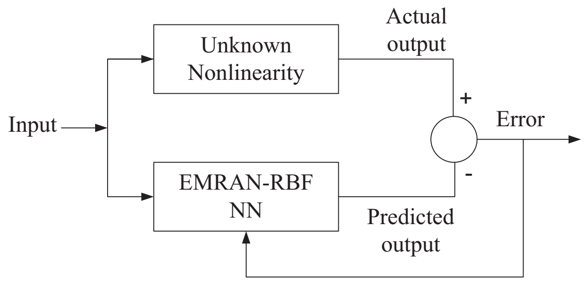

Figure 2: Nonlinearity approximation using EMRAN-RBF NN

3.1 Backlash Approximation

The backlash nonlinearity is shown in Figure 3, and the mathematical model describing it is given by the expression [6]:

$$\dot{u}(t) = \begin{cases} m\,\dot{v}(t) & if\ \dot{v}(t) > 0 \quad and\ u(t) = m(v(t) - c_r) \quad or \\ & if\ \dot{v}(t) < 0 \quad and\ u(t) = m(v(t) - c_l) \\ 0 & \text{otherwise} \end{cases}$$

It can be seen that backlash is a first order velocity driven dynamic system, with inputs $v(t)$ and $\dot{v}(t)$, and state $u(t)$.

The parameters defining the architecture and the corresponding learning parameters for the NN are shown in Table 1. These values are found by trial and error to obtain the best performance for backlash approximation. In the simulation the backlash dead-zone is set to 2. The training performance is measured in terms of mean square error (MSE).

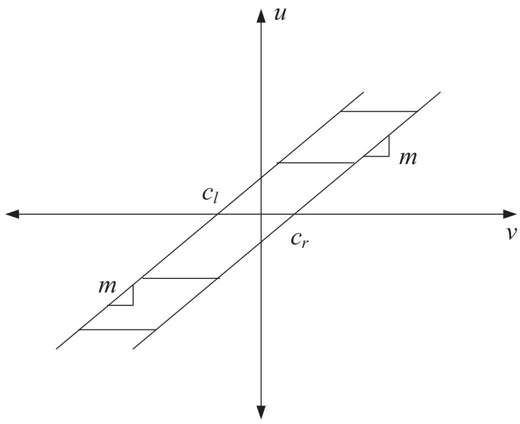

Figure 3 Input-Output Characteristics of Backlash

Table 1: EMRAN-RBFNN Parameters for Backlash Approximation

Parameter	**Value**	**Description**
Maximum number of neurons	4	Limit for the network growth
$[\eta_w\ \ \eta_\sigma\ \ \eta_\mu]$	[0.05 0.01 0.01]	Learning Rates for weights, widths, and centers
$[E_1\ \ E_2\ \ E_3]$	[0.01 0.02 0.01]	Thresholds for three condition of growing criteria
λ	5.2	Activation Overlapping Factor

The training performance of on-line backlash approximation is shown in Figure 4. Assuming a target MSE of 0.01 to compare between the RAN and EMRAN approaches. It can be seen from Figure 4 that when the pruning strategy does not used (RAN), the approximation performance reached the MSE=0.01 at more than 10000 training sample. While, when the pruning strategy is used, the performance reached the MSE=0.01 at only 2410 training sample. The sampling time used in the simulation is (1/1000 sec), thus the network with pruning strategy requires only 2.41 sec to reach to the MSE=0.01, while it requires more than 10 sec for no pruning case. When the network reached the maximum number of neurons, the pruning strategy begins to take effect, keeping the number of hidden neurons not greater than 4 by removing the hidden neurons that makes little contribution to the network output and replace it by a new one in order to avoid excessive increase in the network size. The approximation is improved when the pruning strategy is used since when the conditions of adding a new neuron are satisfied, then the new neuron substitutes the one having the least activation. While for the case of no pruning when the network size reaches the maximum number of neurons, no neuron will be added and only the tuning parameters are updated.

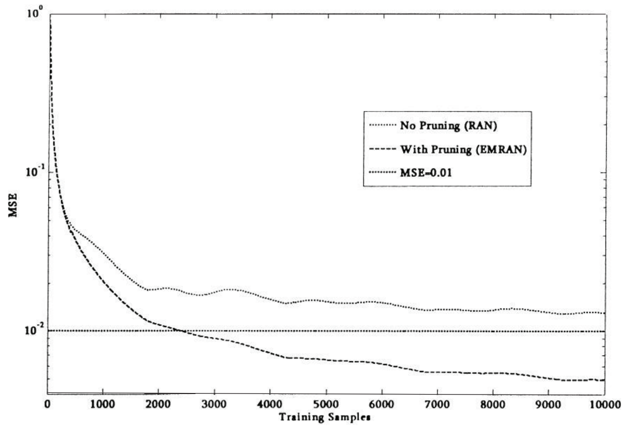

Figure 4 On-line Training Performance of Backlash Approximation

The input-output relationship for the actual and approximated backlash is shown in Figure 5. It is clear that the RBF-NN with EMRAN learning algorithm provides an accurate approximation for the backlash nonlinearity. The response of the actual backlash and the approximated using NN for the sinusoidal input of amplitude and frequency of 10 and 5 Hz, respectively is shown in Figure 6.

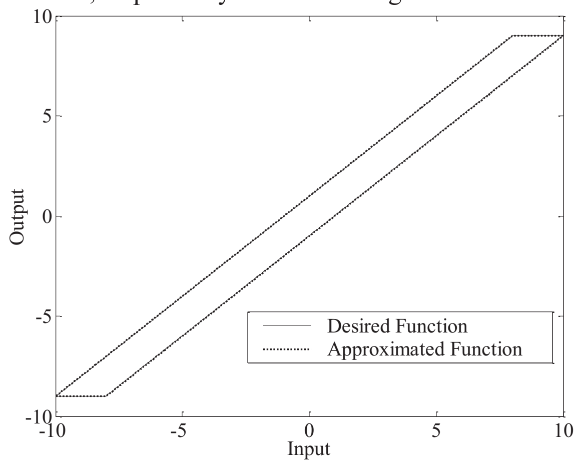

Figure 5 Desired and Approximated Backlash Nonlinearity

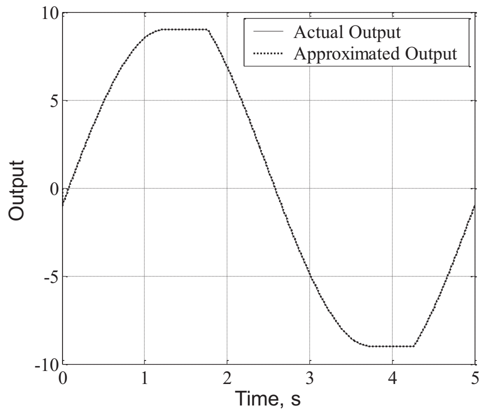

Figure 6 Actual and Approximated Output of Backlash for Sinusoidal Input

4. CONCLUSIONS

For the previous backlash example, and by observing the behaviour of the EMRAN-RBF NN, the following can be concluded:

1. The RBF-NN with EMRAN learning algorithm is good universal approximators for non-smooth nonlinear function.
2. There is no need for a large number of iterations to approximate nonlinear function as in RAN-RBF NN, thus the approximation performance reaches its target within a short time compared with RAN-RBF NN
3. The network does not need large number of neurons because of pruning strategy, thus it has a compact structure.

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